A Computer Algorithm for Sorting Field Data on Fuel Depths

Frank A. Albini

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INTERMOUNTAIN FOREST AND RANGE
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ABSTRACT

Describes an algorithm for separating fuel depth data into distinctive groups of measurements. The algorithm is justified heuristically, through its mathematical similarity to the "tuner" of a radio receiver. Test data generated artificially were used to maximize the sensitivity of the algorithm. The algorithm has been applied successfully to field data gathered by standard fuel inventory procedures, but output should be verified by someone familiar with the sampled area. A rough flow chart and a FORTRAN listing are included. Copies of the computer program are available from the author.

INTRODUCTION

Several published methods for inventorying wildland fuels (Van Wagner 1968; Brown 1971; USDA Forest Service 1974) and another in preparation[1] entail the sampling of fuel depths. The vertical height to the uppermost fuel component is recorded at each of many sample points. When the net of sample points is sufficiently dense, this procedure should approximate the "sheet depth" estimation procedure (Brown 1971); but in some cases the captured information would prohibit the interpretation of it as such without special effort.

To illustrate, consider the following conceptual arrangement of fuel pieces: Dowels, 1 cm in diameter, extending vertically 1 m above the terrain surface, are placed 20 cm apart in a uniform square grid. Using the "sheet depth" estimation procedure, a 1-m average fuel depth would be deduced. If a sampling technique were used, with the sample locations chosen at random, the resulting *average* depth would depend upon the details of the sampling procedure.

One common method of depth sampling is the random selection of points at which samples are to be made. Then a 5-cm radius circle is lowered vertically, with the plane of the circle held horizontally, until the circular area intercepts a fuel element. In our example, the intercept would occur at a height of 1 m if the centerline of a dowel fell within 5.5 cm of the center of the sampling circle. In other words, areas of $\pi(5.5)^2 = 95\ \text{cm}^2$ are selected at random from the general area. If a dowel centerline lies within that area, a depth of 1 m is recorded; if not, a depth of zero is recorded. Since the density of dowel centerlines in the area is one per 400 cm^2, the probability of intercepting a centerline on any given measurement is 95/400, or 0.238. So, for a large enough set of sample points, the recorded fuel depths would be 23.8 percent at 1 m and 76.2 percent at zero, and an average depth of 23.8 cm would be computed.

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[1]Frandsen, William H. A firespread model for spatially nonuniform forest floor fuel arrays. Problem analysis, USDA For. Serv., Intermt. For. and Range Exp. Stn., North. For. Fire Lab., Missoula, Mont. (in preparation).

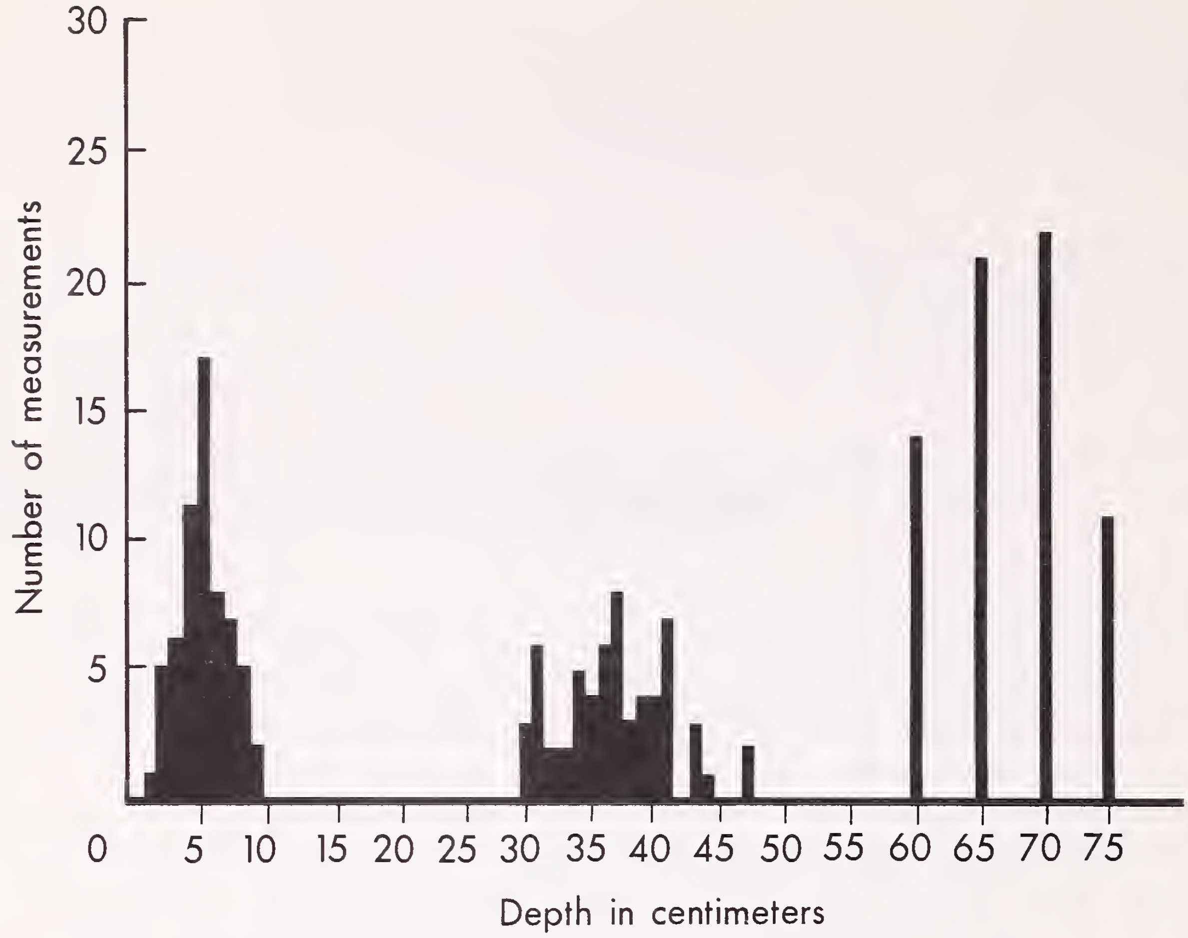


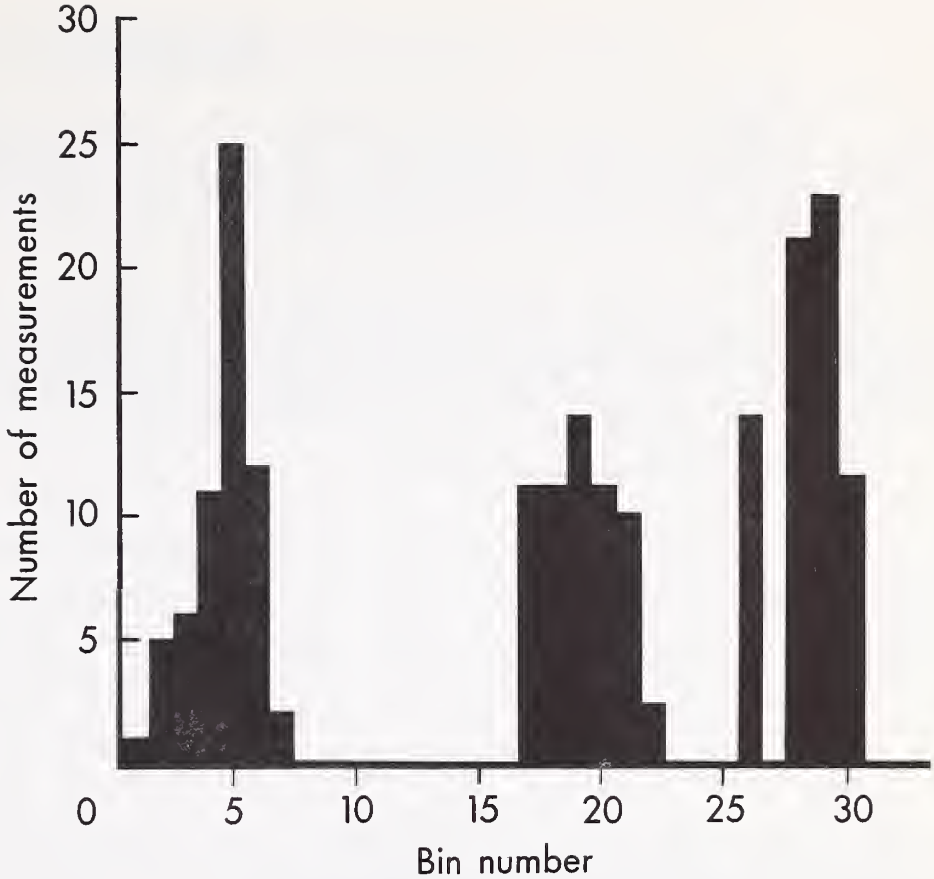
Figure 1.--Histogram of hypothetical depth-measurement data showing three superposed but distinctive groupings of depths.

We could have specified, for instance, that the spread of depths within which a measurement must fall to be included in a given bin should vary linearly with the median depth measurement for each bin. For example, we could increase by 0.1 cm the spread of depths for each successive bin, starting with the smallest, and construct a sequence of partition points as follows: 1.1, 2.3, 3.6, 5.0, 6.5, etc. This would lead to a different histogram (fig. 2).

The procedure just outlined is somewhat arbitrary, but has a least heuristic justification. A measurement resulting in a recorded fuel depth of 2 cm is unlikely to change by 1 cm if repeated. But a measurement of 30 cm could easily become 29 or 31 cm if repeated. Not that the measurements would necessarily be in error, but that minor variations in windspeed, angle of solar illumination, etc., can result in small physical displacements of the fuel elements, and thus change the depth measurements. The greater the fuel depth, the greater the latitude for variations in depth, and the less important are such variations in determining fire behavior.

Two significant features of the revised histogram are that some of the vertical bars have become longer and that the patterns are almost fully contiguous within each group. My subjective view is that the lack of gaps between the vertical bars is an important factor in recognizing groupings. The vertical height of prominent bars also seems to attract the eye and to lead one to recognize the group with the longer bars more readily than the others. It is these two features which have been used as key elements in the algorithm described below, permitting a digital computer to sort raw data--a set of depth measurements—into groups.

Figure 2.--Reconstruction of histogram of figure 1 using variable depth spreads for combining measurements.



If the forms of the distribution functions of the various groups of data are known, a much more sophisticated (and probably more accurate) method of extracting the groups could be used. This would consist of the determination of the Fourier coefficients for a series of distribution functions whose sum represents the histogram. Without knowledge of even the form of the distribution functions, we are forced to turn to cruder means of analysis.

The approach that was taken in formulating the algorithm can be described in the following terms:

1. A set of histograms is constructed, using different numbers of bins, with bin widths varying from essentially constant to rapidly increasing. The variation in bin widths is linear in the sense that the difference between widths of adjacent bins increases linearly with the ordinal numbers of the bins (as in the example above).

2. Each histogram is examined to determine the most prominent group represented on it. This is done by a thresholding procedure, analogous to laying a piece of paper over the bottom of the histogram, with a straight edge horizontal, and sliding it up the page until only one set of contiguous vertical bars project above the edge. On moving the paper downward, the lower the edge of the masking sheet can be brought before a disjoint vertical bar appears above the edge, the more prominent is the visible group.

3. A numerical rating for each histogram is computed. This rating scores the histogram on the basis of the degree of prominence of the prominent group and the compactness of the distribution included in the prominent group. This parameter is described below.

4. The membership in the most prominent group is determined. These measurements are averaged, then deleted from the measurement set. If sufficient data remain, the entire process is repeated to determine the next group.

The algorithm, as currently implemented, is repeated to determine three groups.

Equations

The equations used in implementing the steps outlined above are briefly developed below. Clearly, a major effort of the algorithm implementation was development of the logical framework and the bookkeeping of data manipulation. But, these are not germane to the analytical content and will not be discussed here.

It is assumed here that the data are all integers. If the data were not in integer format, the values could be multiplied by the appropriate power of 10 to make them integers. The maximum value of 200 used here is arbitrary, but represents a reasonable upper limit to ground fuel depth in centimeters.

A. Bin Width Determination

If the largest (integer) value of the depth-measurement data set is H, the smallest S,[2/] the number of bins into which the data are to be partitioned is N, and width of the j^{th} bin is W_j, then

$$\sum_{j=1}^{N} W_j = (H - S) \tag{1}$$

Since it is desired that the width of each successive bin be greater by a constant (a) than the preceding one, we have also

$$W_j = W_{j-1} + a, \text{ or } W_j - W_{j-1} = a \tag{2}$$

Summing equation (2) from j=2 to j=J gives the general form:

$$W_J = W_1 + (J - 1)a \tag{3}$$

Employing the closure constraint (equation 1) determines the value of the width-increase parameter, (a, as a function of W_1, the first bin width, and the other constants of the problem:

$$NW_1 + a\sum_{j=0}^{N=1} j = H - S; \quad a = (H - S - NW_1)/\ (N(N - 1)/2) \tag{4}$$

Note that when

$$W_1 = (H - S)/N \tag{5}$$

the widths remain constant. This is one case that is considered for each value of N. The values of N and W_1 are selected so that a is nonnegative.

Values of N considered are incremented downward from Max (N), where

$$\text{Max}(N) = \text{Min}(200, [H - \text{S}]) \tag{6}$$

in steps of ΔN. This value is clearly arbitrary, but by experimentation, it was found that

$$\Delta N = \text{Max}(1,\ 0.04\ \text{Max}(N)) \tag{7}$$

works adequately.

2/ All zero measurements are purged at the outset.

Values of W_1 considered are incremented upward from $\mathrm{Min}(W_1)$, where

$$\mathrm{Min}(W_1) = (H - S)/N \tag{8}$$

in arbitrary small steps of ΔW_1. The value used was decided by experimentation:

$$\Delta W_1 = 0.075\ \mathrm{Min}(W_1). \tag{9}$$

In its current configuration, the algorithm employs 22 values of N and 22 values of W_1, generating 484 histograms each time a data set is fed to the algorithm. There is a tradeoff between thoroughness and cost (running time). These numbers may in fact be larger than necessary.

B. *Numerical Rating of Histograms*

We desire to establish a numerical rating scheme that will establish a ranking of the various histograms according to how well they exhibit the existence of a prominent grouping of measurements. From general considerations, this scheme should have the following features:

1. All other factors being equal, the greater the fraction of the total number of data points in the histogram that fall into the prominent group (a group must have contiguous vertical bars on a histogram presentation--the prominent group has the tallest vertical bar), the greater should be the score.

2. As a means of establishing the relative degree of prominence of the prominent groups on the different histograms, the score of each should be reduced by the amount of data hidden below the threshold established by the second-most-prominent group on each histogram. So the number of bins contiguous in the prominent group, multiplied by the value of the threshold setting (expressed as a fraction of total data points) should be deducted. This would leave the exposed fraction as the score.

3. To reduce the tendency of such a scoring scheme as outlined in the first two steps to favor ever-wider bin widths, some penalty must be assessed for using wider and wider bins. Else, in the limit, all data would be lumped into a few large, contiguous bins and the effort would fail its purpose. A satisfactory way to assess this penalty is to divide the score defined in step No. 2 by the square root of the sum of the bin widths included in the prominent group.

Taken together, these three considerations lead to a scoring scheme that characterizes group prominence in terms of tall, narrow, contiguous histogram bars that stand farthest above the next-most-prominent group.

For those familiar with the concepts and terminology of radio communications, the analog of the histogram rating score is a "signal-to-noise ratio." In this analogy, the fraction of the total number of depth measurements that lies in a contiguous group projecting above the minimum threshold plays the part of a voltage signal. The noise component in the denominator is the square root of the total width of the bins included in the above-threshold span. Extending this analogy one step further, the algorithm as a whole can be viewed as a procedure for generating a band-pass filter bank that maximizes the signal-to-noise ratio defined in this way.

The equation used for scoring in the algorithm is:

$$S = \left(\sum_{i=J}^{K} n_i/N_T - (K - J + 1)f\right)/([1 + \delta + \sum_{i=J}^{K} W_i])^{\frac{1}{2}} \tag{10}$$

where

S = histogram rating score

n_i = number of data points in bin number i

N_T = total number of data points in histogram

J = smallest ordinal number of bins in contiguous group, each of whose data point count exceeds the threshold number

K = largest ordinal number of bins in contiguous group, each of whose data point count exceeds the threshold number

f = threshold number expressed as a fraction of total data points in histogram. This is, fN_T is the data point count in a disjoint bin which sets the threshold

W_i = width of bin number i

δ = 0.075 W_1, merely a handy small quantity to eliminate spurious roundoff results when the denominator is rounded down to the next lower integer (the 1 is added for similar stability reasons).

$[x]$ = next smaller integer than x. Integer values are used because a unit represents the smallest possible change in a data point value, so the smallest meaningful change in bin width.

C. Sequence of Operations

The sequence of operations in the algorithm described is shown in the flow diagram of figure 3. Most of the logical and bookkeeping details have been suppressed and only the outline of operations is depicted.

Test Cases

Several test cases were used to perfect and exercise the computer program depicted in figure 3. The purpose of these test cases was to establish the ability of the program to discern groups in artificial data generated by computer.

First, a background set of data were generated by selecting random integers between 0 and 100, inclusive. Then three additional sets of data were generated by selecting numbers at random from triangular distributions. The range of these added data points varied from trial to trial, but typically there would be one with a mean in the range 5-10, one with a mean in the range 15-20, and one in the range 60-70. The number of points in the background distribution was varied, as was the number of points in each of the triangular distributions superposed on the background. The purpose of these trials was to determine the point at which the algorithm could no longer discern the superposed triangular-distribution sets of data as distinctive groups against the noise background.

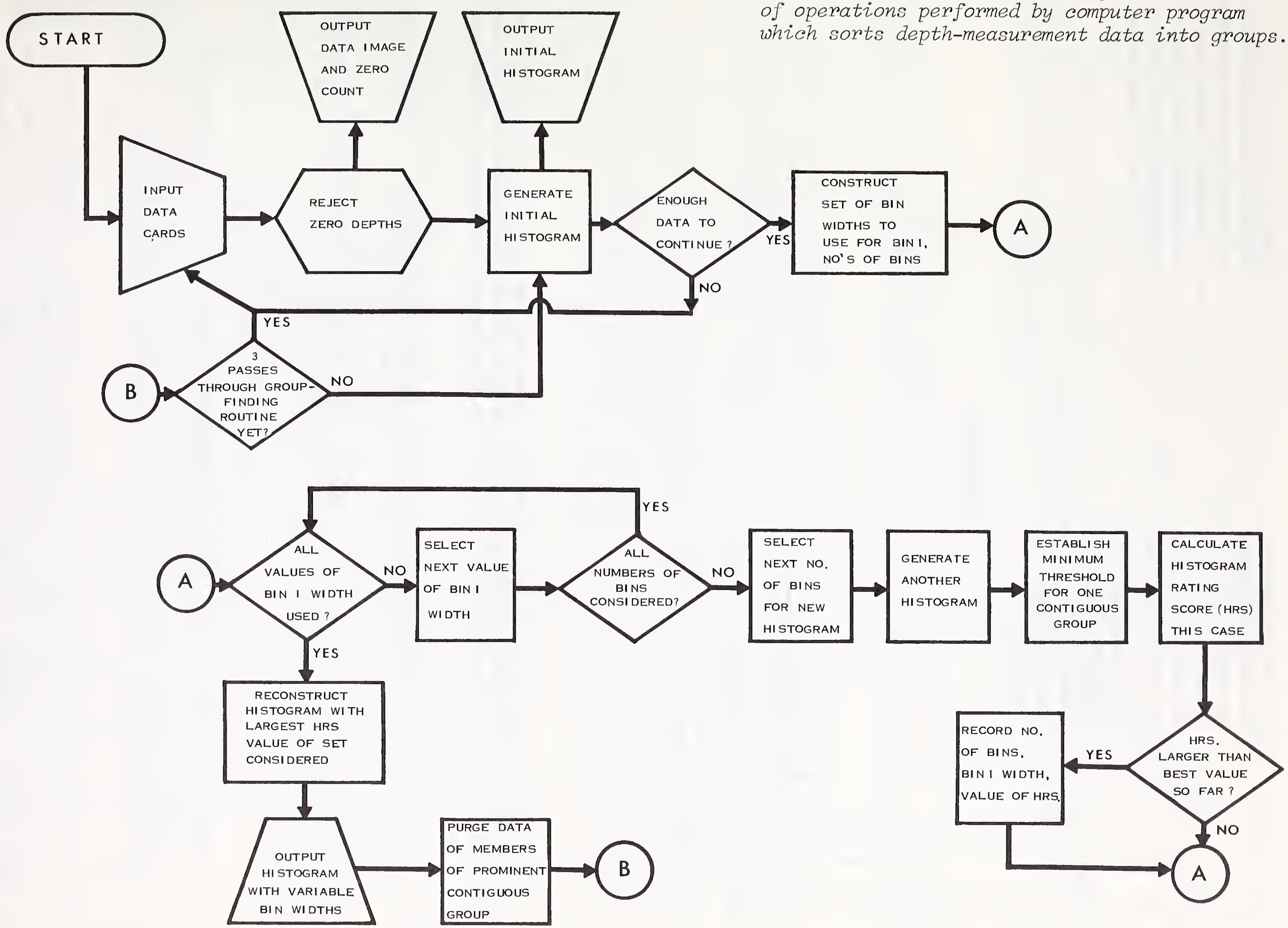


Figure 3.--Flow diagram showing general outline of operations performed by computer program which sorts depth-measurement data into groups.

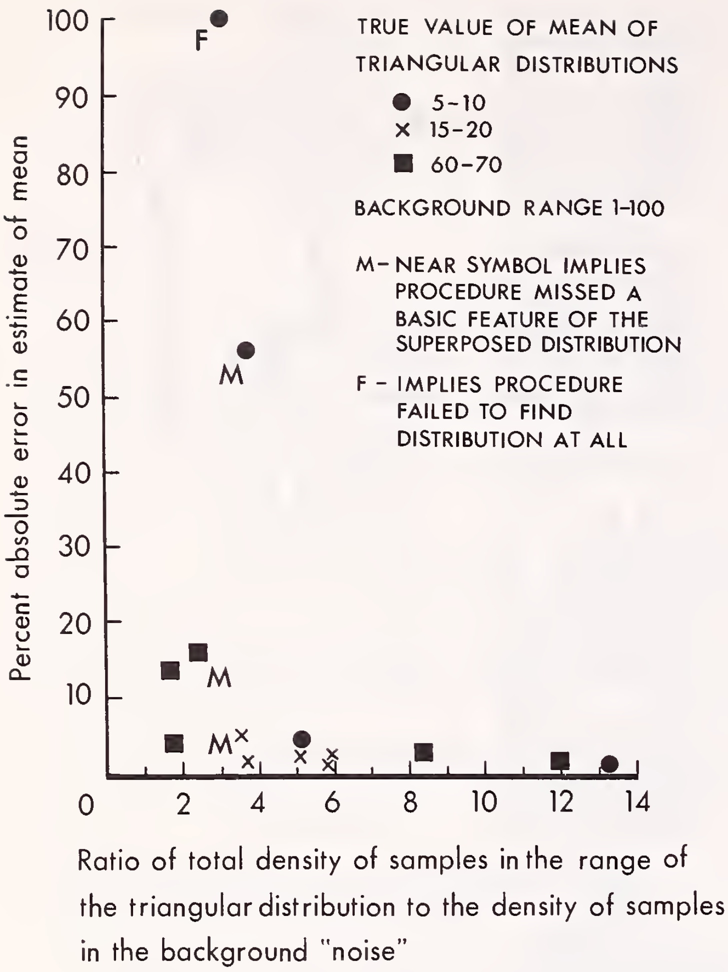


Figure 4.--Accuracy of estimation of distribution mean-versus-density of sample points from triangular distribution superposed on a flat distribution background noise.

The results of these tests were expressed as the percentage error in the estimation of the means of the superposed data groups. A parameter that characterizes the degree to which the superposed distribution is immersed in the background random data is the ratio, R, where

$$R = \frac{\text{Density of data points in range of added distribution}}{\text{Density of data points in the background data set}} \qquad (11)$$

The density of data points is here defined to be the total number of data points in a specified range of values, divided by the span of values in that range. For example, in the case represented by:

1. One hundred random data points in the range 0-100 (background)

2. Twenty data points added from a triangular distribution in the range 10-20

3. Suppose seven of the random data points also fell in the range 10-20; the density of data points in the range of the added distribution would be (20 + 7)/(20 - 10) = 2.7. The density of data points in the background data set would be (100)/(100 - 0) = 1.0, so R = 2.7/1.0 = 2.7.

This ratio is used as the abscissa of the scatter diagram plotted in figure 4. This figure shows all the test case exercises of the group-finding algorithm. The algorithm exhibits the tendency characteristic of its electrical analog discussed above, namely that it either works very well or fails dramatically, and that this failure is to be expected around a value of 3 or 4 for the ratio defined above.

Note that in all cases where the ratio R is greater than 4, the algorithm discovered the superposed distributions and established their mean values with an error less than 5 percent. Of the seven cases shown with R less than 4, two distributions were recovered and their means established with accuracy better than 5 percent; one was recovered but the mean was 13 percent in error; three were not recovered accurately, although their means were estimated (one with 5 percent error, one with 17 percent error, and one with 57 percent); and one distribution was not recovered at all.

Because the performance of the algorithm closely paralleled that which would have been expected on the basis of the analogy that was used in constructing it, no further developmental work was done. The procedure has been used on actual field data as discussed in the following section.

Field Data

As part of the White Cap Drainage Wilderness Fire Management Study,[3] fuel inventory data were taken in 1971, 1972, and 1973. The data were reduced to punched-card formats, categorized by timber cover type and by ecological (climax tree species/understory species) habitat type.[4]

We hoped to exercise Rothermel's spread rate model against these data to help establish prescription guidelines for fire management in the study area. To do so required not only fuel loading data but representative fuel depth estimates. Because the field data did not include the nature of the fuel that resulted in the recorded depths, some sorting procedure was necessary.

The automated procedure outlined above was used with these data, resulting in a set of depth-groups for each habitat type and timber type. These abbreviated data were then reviewed for consistency and to see if the discovered distributions were really representative of the areas in question. Persons familiar with the general regions under investigation could review these output data much more readily than they could the raw data.

In perhaps two-thirds of the cases reviewed, the depth-groupings recovered by the algorithm were acceptable to the reviewers. In the other cases, the consensus was that the algorithm had failed to group the data in a meaningful way.

Some outputs are obviously spurious even to someone unfamiliar with the area under investigation. An example of such a result occurred in the grand fir timber type (dead fuel) exercise. This data set consisted of 780 data points, ranging from zero (40 points) to 200 cm, the greatest depth recorded (16 points). The algorithm first recovered a grouping of 488 data points between 1 and 6 cm with an average depth of 10.46. This left 117 data points scattered between 18 and 200 cm, of which the obviously most prominent group was the concentration of 16 data points at 200 cm. This last group was clearly spurious. On other exercises of the algorithm, more subtle but still spurious results were detected.

In most cases the algorithm appeared to have worked well in recovering one or two groups from the raw data. Frequently a third attempt yielded spurious results; often the data were insufficient to substantiate the existence of a third significant distinctive group.

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[3]Aldrich, David F., and Robert W. Mutch. Fire management prescriptions: a model plan for wilderness ecosystems. USDA For. Serv., Intermt. For. and Range Exp. Stn. (In preparation.)

[4]Pfister, R. D., B. L. Kovalick, S. A. Arno, and R. C. Presby. Forest habitat types of Montana. USDA For. Serv., Intermt. For. and Range Exp. Stn. (In preparation.)

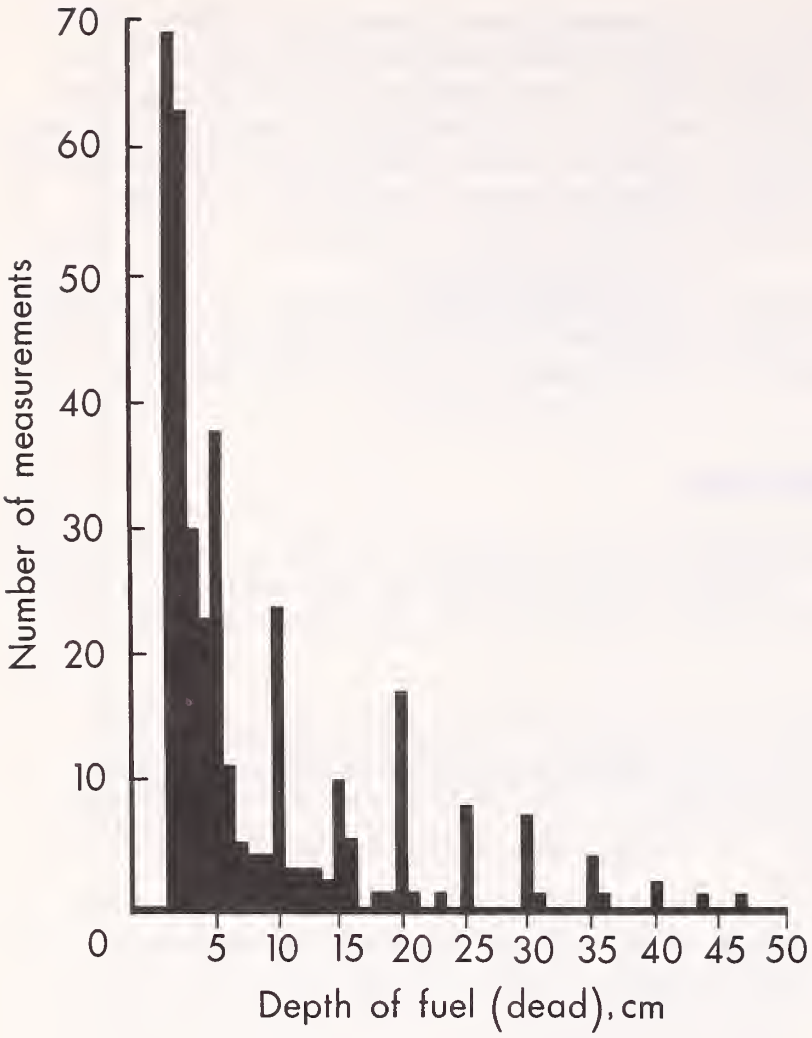


Figure 5.--Histogram of dead fuel depth measurements less than 50 cm taken in lodgepole pine timber type area of White Cap Drainage Wilderness Fire Management Study.

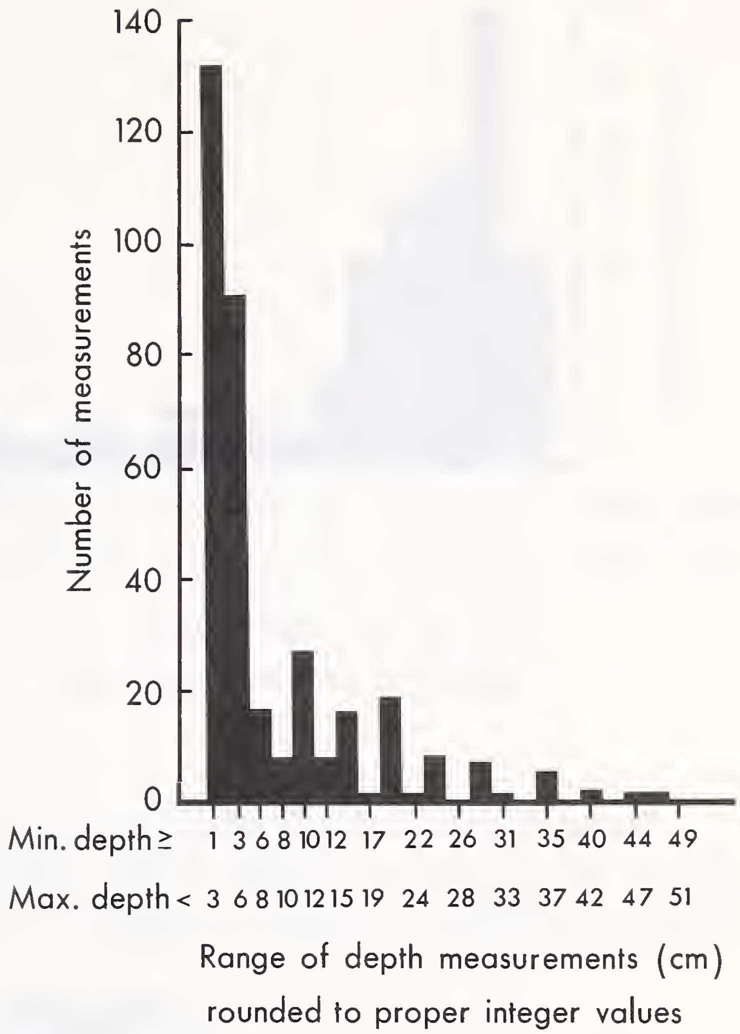
An example of such an exercise is the lodgepole pine timber type (dead fuel only) data from the cited study. These data consisted of 396 depth samples from zero to 190 cm, which included 35 zero-depth data points and the erroneous replication of 6 points. Of the 361 nonzero data points processed by the algorithm, all but 18 were measurements of less than 50 cm. These 18 points were widely scattered--the only concentrations being 3 points at 59-60 cm, and 3 at 90 cm (1 a spurious replicate). The less than 50-cm data are shown in the histogram of figure 5.

These data were processed by the algorithm, resulting in the tapered bin width histogram of figure 6. In this histogram, a prominent group is clearly evident. This group has an average depth of 2.54 cm and contains 223 data points.

The histogram of the remaining 138 (120 below 50 cm) data points is shown in figure 7. Once more these data were processed by the algorithm, resulting in the modified histogram shown in figure 8. Again, a contiguous group is clearly evident in the modified histogram, which shows all the data because the scale is so contracted here. The group apparent in the latter histogram averages 16.04 cm in depth and contains 118 data points.

The remaining 20 data points were processed again, resulting in a spurious group of 3 data points at 90 cm. This last group was rejected, but the other two groups were found to be acceptable as representative of needle litter-mat and fallen dead woody material, respectively.

Figure 6.--Histogram of figure 5 as reconstructed by group-finding algorithm. Prominent group in first two bins contains 223 data points.



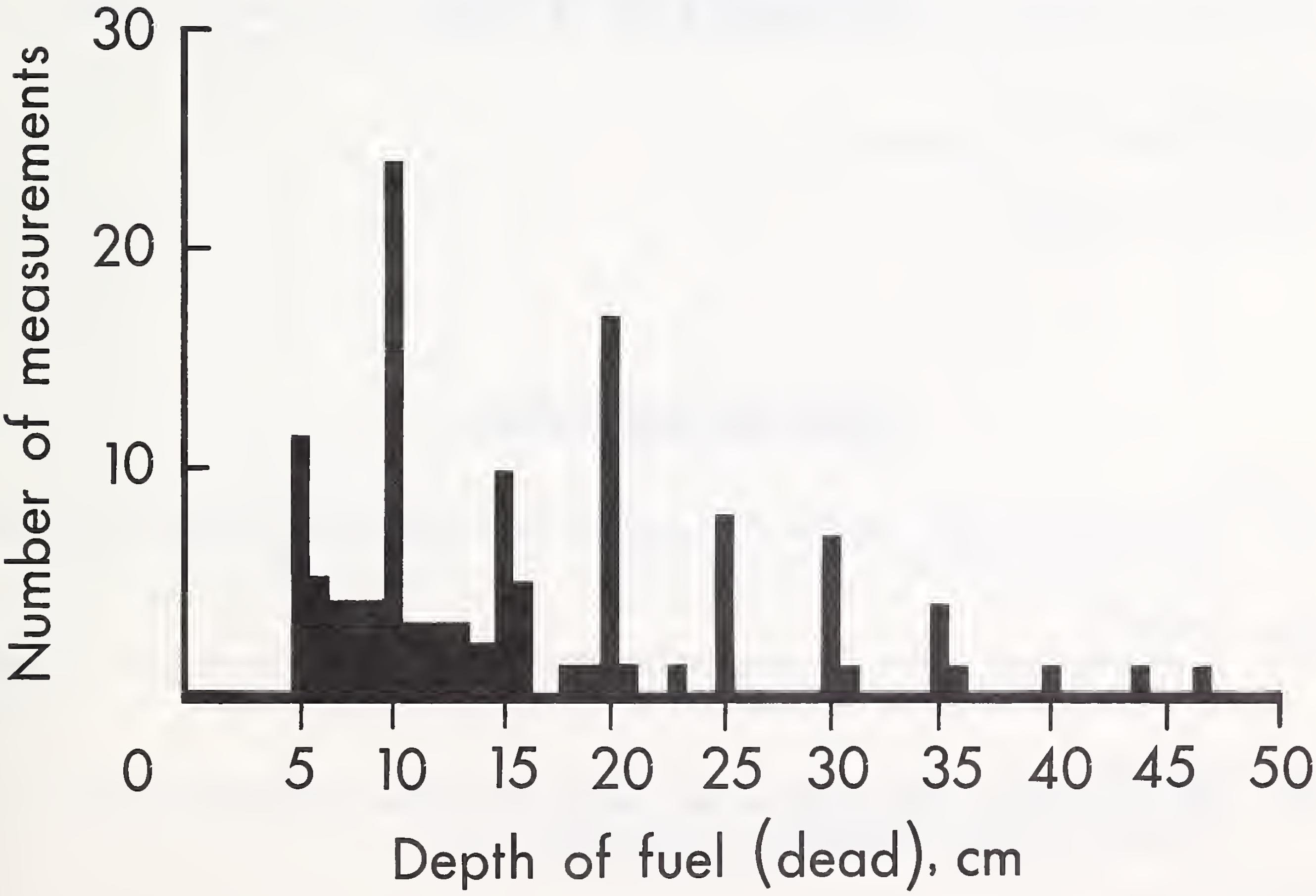


Figure 7.--Histogram of figure 5 after removal of 1-5 cm group.

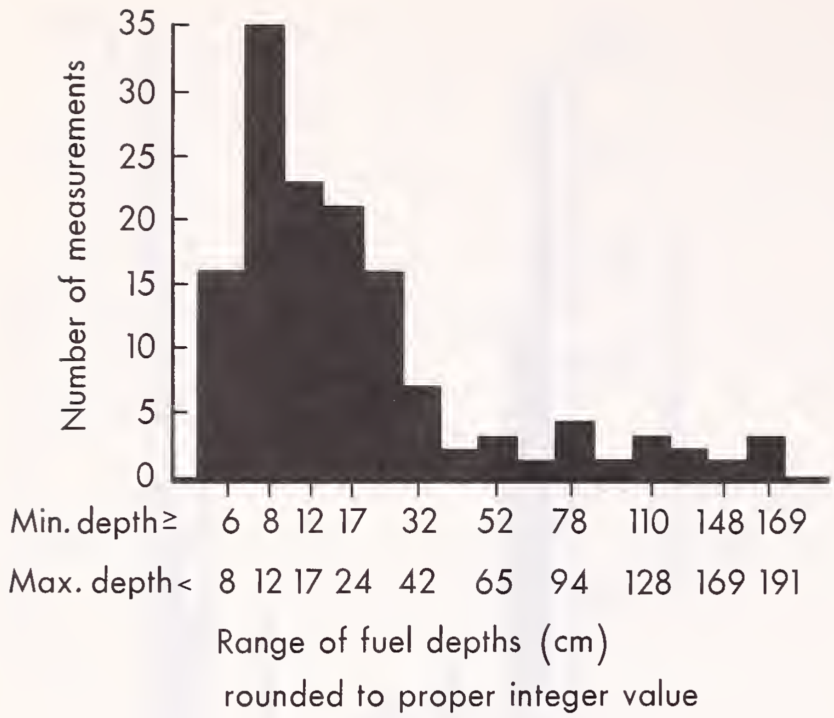


Figure 8.--Histogram of figure 7 (extended to include all data) as reconstructed by group-finding algorithm. Prominent group in first six bins contains 118 data points.

Computer processing of these data greatly expedited the chore of establishing representative depths for fuel arrays characteristic of various areas in the study region. Augmented by judicious review of the computer output, this method may be useful to other researchers holding similar sets of data.

Program Available

The computer program listing (FORTRAN IV) is given in the appendix. Copies of the program may be obtained by contacting the author at the following address:

USDA Forest Service
Northern Forest Fire Laboratory
Drawer G
Missoula, MT 59801

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Brown, James K.
1971. A planar intersect method for sampling fuel volume and surface area. For. Sci. 17(1):96-102.

Rothermel, Richard C.
1972. A mathematical model for predicting fire spread in wildland fuels. USDA For. Serv. Res. Pap. INT-115, 40 p.

USDA Forest Service.
1974. National fuel classification and inventory system: preliminary draft. 24 p. Division of Fire Management, Washington, D.C.

Van Wagner, C. E.
1968. The line intersect method in forest fuel sampling. For. Sci. 14:20-26.

APPENDIX

```
      PROGRAM GROUR (INPUT,OUTPUT,TAPE5=INPUT)

      COMMON X(2000),W(200),NO(200),FR(200),L,LL,S,H,IDS(200),NPTS,NX,FL
      COMMON/INDATA/XIN(9600,3),NPLT(20),IDP(20,700),NAME(20,10),NCASES

   88 CALL READER
      DO 100 NC = 1,NCASES
      NPL = NPLT(NC)
      PRINT 1,NC,(NAME(NC,J),J=1,10)
    1 FORMAT(1H1/10X*CASE NO.*I3/25X,10A8//20X*PLOTS INCLUDED AND DATA*)
    2 FORMAT(I10,3F10.1)
      NX = NPTS = L = LL = 0
      FL = S = H = 0.
      DO 3 J = 1,200
      NO(J) = IDS(J) = 0
      FR(J) = W(J) = 0.
    3 CONTINUE
      DO 4 J = 1,2000
      X(J) = 0.
    4 CONTINUE
      DO 6 I = 1,NPL
      K = IDP(NC,I)
      DO 5 J = 1,3
      NX = NX + 1  $  X(NX) = XIN(K,J)
    5 CONTINUE
    6 PRINT 2,K,(XIN(K,J),J=1,3)
      NXS = NX
      CALL ZILCH(FLAG,ZEROES)
      NZO = NXS - NX
      PRINT 7,NXS,NZO,ZEROES,NX
    7 FORMAT(//10X*THESE*I5*  DATA POINTS INCLUDE*I5*  WITH ZERO OR NEGA
     1TIVE VALUES*/10X*OR A FRACTION OF*F7.4*  OF THE DATA.  THESE HAVE
     2BEEN EXPUNGED, LEAVING*I5*  POINTS*)
       IF(FLAG.EQ.0.) GO TO 9
      PRINT 8
    8 FORMAT(10X*THIS BEING TOO LITTLE DATA. THIS CASE IS SKIPPED*)
```

```
      GO TO 100
    9 CALL PULLER
  100 CONTINUE
      GO TO 88
      END



      SUBROUTINE READER

      COMMON X(2000),W(200),NO(200),FR(200),L,LL,S,H,IDS(200),NPTS,NX,FL
      COMMON/INDATA/XIN(9600,3),NPLT(20),IDP(20,700),NAME(20,10),NCASES

C     THIS SUBROUTINE READS IN THE DATA FOR A SERIES OF RUNS.....
C     THE VARIABLES ARE PASSED TO THE FUNCTIONAL ROUTINES THROUGH COMMON

C     THE NUMBER OF CASES TO BE RUN IS      NCASES.... COUNTED ON INPUT HERE

C     THE NUMBER OF PLOTS PER CASE IS       NPLT(J)     J IS THE CASE NUMBER

C     THE NAME OF THE RUN IS GIVEN AS      NAME(J,I)

C     THE IDENTITY OF PLOT NUMBER K FOR CASE J IS     IDP(J,K)

C     THE DEPTH SAMPLE INPUT DATA ARE ENTERED INTO ARRAY XIN(I,J)
```

```
      SUBROUTINE ZILCH(FLAG,ZEROES)
C  ..  FLAG=0, NO TROUBLE. =1, NOT ENOUGH POINTS LEFT TO ANALYZE
      COMMON X(2000),W(200),NO(200),FR(200),L,LL,S,H,IDS(200),NPTS,NX,FL
      NEX = 0  $  FLAG = 0.  $  ZEROES = 0.
      DO 10 J = 1,NX
      IF(X(J).LE.0.) GO TO 10
      NEX = NEX + 1  $  X(NEX) = X(J)
   10 CONTINUE
      NEXT = NEX + 1
      DO 20 J = NEXT,2000
      X(J) = 0.
   20 CONTINUE
      NGONE = NX-NEX  $  ZEROES = FLOAT(NGONE)/FLOAT(NX)
      IF(NEX.LE.4)  FLAG = 1.
      NX = NEX  $  RETURN  $  END


      SUBROUTINE THRESH(FLAG,FINC)
      COMMON X(2000),W(200),NO(200),FR(200),L,LL,S,H,IDS(200),NPTS,NX,FL
      FLAG=0.  $  NL=NO(1)
      DO 1 J = 2,NPTS
      IF(NO(J).GT.NL) NL = NO(J)
    1 CONTINUE
      NL = NL-1  $  NUP=0  $  FINC=0.  $  NA=NO(2)  $  NB=NO(NPTS-1)
      IF(NL.LE.0)  GO TO 10
      DO 2 J = 1,NPTS
      IF(NO(J)-NL) 2,22,222
```

```
222   NUP = NUP + 1 $ IDS(NUP) = J $ FINC = FINC + FR(J) $ GO TO 2
 22   IF(J.EQ.1) GO TO 32
      IF(J.EQ.NPTS) GO TO 42
      IF((NO(J-1).GE.NL).OR.(NO(J+1).GE.NL))222,2
 32   IF(NA.GE.NL) 222,2
 42   IF(NB.GE.NL) GO TO 222
  2   CONTINUE
      NTHRU = IDS(NUP) - IDS(1) + 1
      IF(NTHRU.NE.NUP)  GO TO 10
      NL = NL - 1
      IF(NL.GT.0) GO TO 4
      L=IDS(1)  $  LL=IDS(NUP)  $  FL=FLOAT(NL+1)/FLOAT(NX)  $  RETURN
  3   NL = NL -1
      IF(NL.LE.0) GO TO 7
  4   NUP = 0  $  FINC = 0.
      DO 5 J = 1,NPTS
      IF(NO(J)-NL) 5,55,555
555   NUP = NUP + 1 $ IDS(NUP) = J $ FINC = FINC + FR(J) $ GO TO 5
 55   IF(J.EQ.1) GO TO 35
      IF(J.EQ.NPTS) GO TO 45
      IF((NO(J-1).GE.NL).OR.(NO(J+1).GE.NL)) 555,5
 35   IF(NA.GE.NL) 555,5
 45   IF(NB.GE.NL) GO TO 555
  5   CONTINUE
      NTHRU = IDS(NUP) - IDS(1) + 1
      IF(NTHRU.EQ.NUP)  GO TO 3
  6   NL = NL + 1
      IF(NL.GE.NX) 10,8
  7   NL = NL + 1
      FL=FLOAT(NL)/FLOAT(NX)  $  L=IDS(1)  $  LL = IDS(NUP)
      IF(FL.LT.0.)  FL = 0.
      RETURN
  8   NUP = 0  $  FINC = 0.
      DO 9 J = 1,NPTS
      IF(NO(J)-NL) 9,99,999
999   NUP = NUP + 1 $ IDS(NUP) = J $ FINC = FINC + FR(J) $ GO TO 9
```

```
99   IF(J.EQ.1) GO TO 39
     IF(J.EQ.NPTS) GO TO 49
     IF((NO(J-1).GE.NL).OR.(NO(J+1).GE.NL)) 999,9
39   IF(NA.GE.NL) 999,9
49   IF(NB.GE.NL) GO TO 999
 9   CONTINUE
     NTHRU=IDS(NUP)-IDS(1)+1  $  FL=FLOAT(NL)/FLOAT(NX)
     IF(NTHRU.NE.NUP)  GO TO 10
     L = IDS(1)  $  LL = IDS(NUP)  $  RETURN
10   FLAG = 1.  $  RETURN  $  END




     SUBROUTINE HGRAM

     COMMON X(2000),W(200),NO(200),FR(200),L,LL,S,H,IDS(200),NPTS,NX,FL

     DO 1 J = 1,NPTS
     NO(J) = 0  $  FR(J) = 0.
1    CONTINUE
     XMAX = S  $  XNX = FLOAT(NX)
     DO 4 I = 1,NPTS
     XMIN = XMAX  $  XMAX = XMIN + W(I)
     IF(I.EQ.NPTS)  XMAX = 1.00101*XMAX
     DO 3 J = 1,NX
     T = X(J)
     IF((T.LT.XMIN).OR.(T.GE.XMAX))  GO TO 3
     NO(I) = NO(I) + 1
3    CONTINUE
4    FR(I) = FLOAT(NO(I))/XNX
     RETURN  $  END
```

```
      SUBROUTINE WINDOW(FLAG)

      COMMON X(2000),W(200),NO(200),FR(200),L,LL,S,H,IDS(200),NPTS,NX,FL

C     FLAG = 0. NO TROUBLE. 1.SINGULAR DISTRIBUTION. 3. NO SOLUTION

      XMIN = S  $  XMAX = H  $  FLAG = 0.
      IF((NPTS.LE.1).OR.((S+W(1)).GE.H))  GO TO 3
      WN = FLOAT(NPTS)
      A = (XMAX - XMIN - WN*W(1))*2./(WN*(WN-1.))
      IF(A.LE.0.)  GO TO 4
      DO 2 J = 2,NPTS
      W(J) = W(J-1) + A
    2 CONTINUE
      RETURN
    3 NPTS = 1  $  FLAG = 1.  $  RETURN
    4 FLAG = 2.  $  RETURN  $  END




      SUBROUTINE TUNER(SNB)

      COMMON X(2000),W(200),NO(200),FR(200),L,LL,S,H,IDS(200),NPTS,NX,FL

      DIMENSION TS(22),FIN(22),W1(22),IL(22),IH(22),NBINS(22),SN(22)
      NB = 0 $ NPS = 0 $ SNB = 0. $ W1B = 0.
      W1(1) = W(1)  $  DW = .075*W(1)
      DO 1 J = 2,22
      W1(J) = W1(J-1) + DW
    1 CONTINUE
      DO 9 J = 1,22
      W(1) = W1(J)
      DO 2 K = 1,22
      TS(K) = FIN(K) = SN(K) = 0.
```

```
      IL(K) = IH(K) = 0
 2    CONTINUE
      NPMX=(H-S)/W(1)  $  NPMX=MIN0(NPMX,200)  $  NPMX=MAX0(NPMX,3)
 3    CALL WINDOW(FLAG)
      IF(FLAG.EQ.1.)  GO TO 9
      IF(FLAG.NE.2.)  GO TO 4
      NPMX = NPMX - 1
      IF(NPMX.LT.3) 9,3
 4    DN = .04*FLOAT(NPMX)  $  ND = DN
      IF(ND.LT.1)  ND = 1
      NPTS = NPMX + ND
      DO 7 K = 1,22
      NPTS = NPTS - ND  $  NBINS(K) = NPTS
      IF(NPTS.LT.3)  GO TO 7
      CALL WINDOW(FLAG)
      IF(FLAG.EQ.2.) GO TO 7
      IF(FLAG.EQ.1.) GO TO 6
      CALL HGRAM
      CALL THRESH(FLG,FINC)
      IF(FLG.NE.0.)  GO TO 7
      IL(K) = L  $  IH(K) = LL  $  FIN(K) = FINC  $  TS(K) = FL
      WIDE = 0.
      DO 5 I = L,LL
      WIDE = WIDE + W(I)
 5    CONTINUE
      WIDE = WIDE + 1.+DW
      NWIDE = WIDE  $  WIDE = FLOAT(NWIDE)
      SN(K)=(FIN(K)-TS(K)*FLOAT(LL+1-L))/SQRT(WIDE)  $  GO TO 7
 6    IL(K) = 1 $ IH(K) = NPTS $ FIN(K) = 1. $ TS(K) = 0.
      SN(K) = 1./SQRT(H-S)
 7    CONTINUE
      DO 8 K = 1,22
      IF(SN(K).LE.SNB)  GO TO 8
      SNB = SN(K) $ W1B = W1(J) $ NB = NBINS(K)
 8    CONTINUE
 9    CONTINUE
```

```
      NPTS = NB  $  W(1) = W1B
      CALL WINDOW(FLAG)
      IF(FLAG.NE.0.)  GO TO 10
      CALL HGRAM
      RETURN
10    PRINT 11
11    FORMAT(///10X*TROUBLE IN TUNER ROUTINE*)
      SNR = -1.  $  RETURN  $  END



      SUBROUTINE PULLER

      COMMON X(2000),W(200),NO(200),FR(200),L,LL,S,H,IDS(200),NPTS,NX,FL

      DIMENSION NAST(80)
      DATA(NAST=80(1H*))
      NPULLS = 0
100   S = X(1)  $  H = X(1)  $  NPULLS = NPULLS + 1
      DO 1 J = 2,NX
      T = X(J)
      IF(T.LT.S) S = T
      IF(T.GT.H) H = T
1     CONTINUE
      DB=.0025*(H-S)  $  H=H+DB  $  S = S - DB
      PTS=H-S $ NPTS=PTS+1.01 $ NPTS=MAX0(NPTS,2) $ NPTS=MIN0(NPTS,200)
      W(1) = (H-S)/FLOAT(NPTS)
2     CALL WINDOW(FLAG)
      IF(FLAG.EQ.2.)  GO TO 4
      CALL HGRAM
      PRINT 10
10    FORMAT(1H1/10X*INITIAL HISTOGRAM OF DATA*//
     15X*BIN*5X*COMPARTMENT LIMITS*5X*NUMBER*5X*RELATIVE*/
     25X*NO.*5X*LOWER - TO - UPPER*5X*POINTS*5X*FREQUENCY*//)
```

```
 20   FORMAT(I8,F10.2,F13.2,I9,F15.5,5X,80A1)
      X2 = S
      DO 3 J = 1,NPTS
      X1=X2  $  X2=X1+W(J)  $  NA=NO(J)  $  NA=MINO(NA,80)
      IF(NA.LE.0)  GO TO 3333
      PRINT 20,J,X1,X2,NO(J),FR(J),(NAST(K),K=1,NA)
      GO TO 3
3333  PRINT 20,J,X1,X2,NO(J),FR(J)
 3    CONTINUE
      GO TO 5
 4    W(1) = .9999999*W(1)  $  GO TO 2
 5    CALL TUNER(SNB)
      IF(SNB.LE.0.)  GO TO 101
      CALL THRESH(FLAG,FINC)
      IF(FLAG.EQ.1.) GO TO 101
      PRINT 30,FINC
 30   FORMAT(1H1//10X*HISTOGRAM WITH TAPERED COMPARTMENTS REVEALS GROUP*
     1//10X*PROMINENT CONTIGUOUS GROUP CONTAINS*F7.5* OF POINTS*///
     15X*BIN*5X*COMPARTMENT LIMITS*5X*NUMBER*5X*RELATIVE*/
     25X*NO.*5X*LOWER - TO - UPPER*5X*POINTS*5X*FREQUENCY*//)
      X2 = S
      DO 6 J = 1,NPTS
      X1=X2  $  X2=X1+W(J)  $  NA=NO(J)  $  NA = MINO(NA,80)
      IF(NA.LE.0)  GO TO 6666
      PRINT 20,J,X1,X2,NO(J),FR(J),(NAST(K),K=1,NA)
      GO TO 6
6666  PRINT 20,J,X1,X2,NO(J),FR(J)
 6    CONTINUE
      PRINT 40,L,LL
 40   FORMAT(//5X*NOTE GROUP IN COMPARTMENTS*I4* TO*I4)
      XLOW = S  $  ML = L-1
      IF(L.EQ.1) GO TO 8
      DO 7 J = 1,ML
      XLOW = XLOW + W(J)
 7    CONTINUE
 8    XHIGH = XLOW
```

```
      DO 9 J = L,LL
      XHIGH = XHIGH + W(J)
9     CONTINUE
      K = 0  $  NEW = 0  $  SUM = 0.
      DO 12 J = 1,NX
      IF((X(J).GE.XLOW).AND.(X(J).LE.XHIGH))  GO TO 11
      K = K + 1  $  NEW = NEW + 1  $  X(K) = X(J)  $  GO TO 12
11    SUM = SUM + X(J)
12    CONTINUE
      AV = SUM/FLOAT(NX - NEW)
      PRINT 50, AV
50    FORMAT(//5X*AVERAGE OF INCLUDED DATA POINTS (NOW REMOVED)*F15.5)
      NX = NEW
      PRINT 60, NEW
60    FORMAT(//5X*TOTAL REMAINING POINTS*I5)
      IF((NPULLS.LE.2).AND.(NX.GT.4))  GO TO 100
      IF(NPULLS.LT.3) PRINT 80
80    FORMAT(10X*INSUFFICIENT DATA TO CONTINUE SEARCH FOR GROUPS*)
      RETURN
101   PRINT 70
70    FORMAT(///10X*UNABLE TO DETERMINE GROUPING ON THIS DATA*)
      RETURN  $  END
```


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ALBINI, FRANK A.
1975. A computer algorithm for sorting field data on fuel depths. USDA For. Serv. Gen. Tech. Rep. INT-23, 25 p. (Intermountain Forest and Range Experiment Station, Ogden, Utah 84401.)

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